

AIAA SciTech 2016



Machine Intelligence for Unmanned Systems at NASA Langley Research Center's Autonomy Incubator

B. Danette Allen, PhD Head, Autonomy Incubator NASA Langley Research Center 05 January 2016



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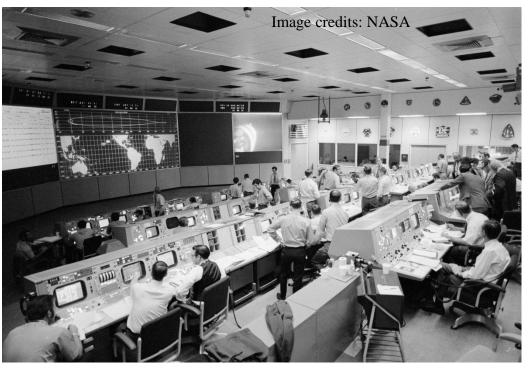


NASA's Manned Missions



 Historic and current ATM and space exploration paradigms are human-centric. Humans are aided by automation to make intelligent decisions and intervene as needed, especially in off-nominal situations.





Five of the seven Apollo missions that attempted to land on the Moon required real-time communications with controllers to succeed.



NASA's Unmanned Missions



 Historic and current ATM and space exploration paradigms are human-centric. Humans are aided by automation to make intelligent decisions and intervene as needed, especially in off-nominal situations.





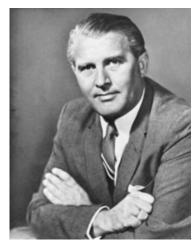
Things have changed but... humans are still hovering around monitors waiting to intervene.



Human Intelligence



 "The best computer is a man, and it's the only one that can be mass-produced by unskilled labor." — Wernher von Braun





- Apollo 13 Control Room
- Gene Kranz "in a box"?

Image credits: NASA



Machine/Artificial Intelligence



Credit: http://xkcd.com/1425/



IN CS, IT CAN BE HARD TO EXPLAIN THE DIFFERENCE BETWEEN THE EASY AND THE VIRTUALLY IMPOSSIBLE.

Finding the Bird



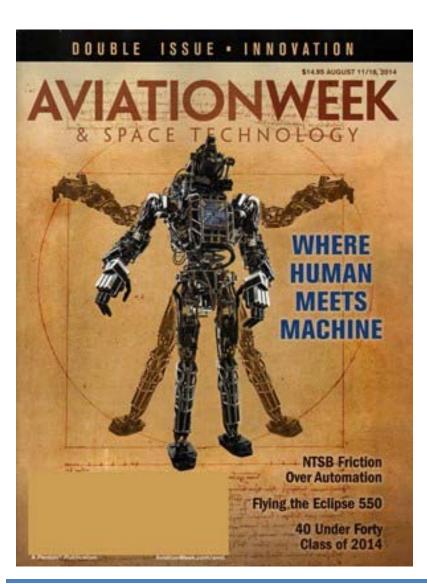
In the 60s, Marvin Minsky assigned a couple of undergrads to spend the summer programming a computer to **use a camera to identify objects** in a scene. He figured they'd have the problem solved by the end of the summer. Half a century later, we're still working on it.

This work [xkcd] is licensed under a Creative Commons Attribution-NonCommercial 2.5 License.



Autonomy and Intelligence





Automation vs. Autonomy

"There is a paradigm shift from automated to autonomous: **automation is relegation**; **autonomy is delegation**..."

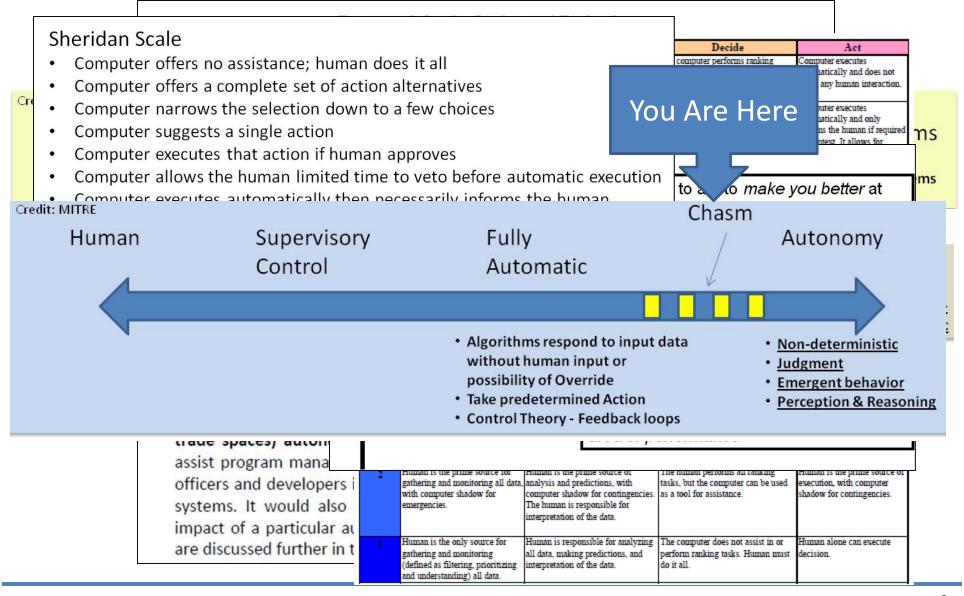
"... safe and trusted systems than can perceive their environment for situational awareness and assessment, make decisions on uncertain and inaccurate information, act appropriately, learn from experience and adapt their behavior..."

"...[certification] is about **behavior and probability**... we will need new methods of verification and validation."



The Autonomy Chasm







Why Autonomy Seems Easy...



- It's a simple problem to relate to
- It has a little bit of everything
 - Mechanics
 - Electronics
 - Programming
 - Psychology
 - Signal Processing
 - Controls
 - Math

— ...



Why Don't You Just...



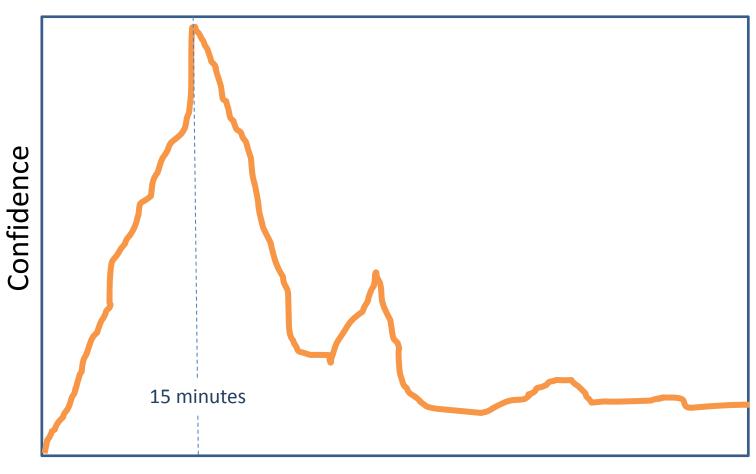
- Negotiate the mission?
- Swarm?
- Self-separate?
- Fuse multiple sources of information?
- Put the human on the loop?
- Pull the human out of the loop?
- Detect a target?
- Find the bird...



The 15-Minute Effect







Time

BD Allen, G Bishop, G Welch, "Tracking: Beyond 15 Minutes of Thought" Proceedings of the 28th Annual SIGGRAPH Conference, 2001.



At 15 Minutes



Autonomy "Main is Hard" **

** Credit: Barbie



Why Autonomy?



- Effectiveness
- Efficiency
- Assistance
- Companionship
- Manipulation
- Safety
- The "ilities"
 - Adaptability
 - Affordability
 - Accessibility
 - Agility
 - Flexibility
 - Mobility
 - Scalability
 - Reliability

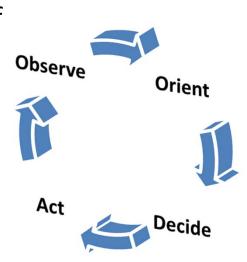




NASA's Missions and Autonomy



- Human intelligence applied to supervision, control, and intervention of operations will no longer be viable due to system/mission complexity, short reaction/decision time, communication delays, distance, or hostile environments.
- Systems with machine intelligence: capable of responding to expected and unexpected situations:
 - trusted and certified-safe systems capable of
 - sensing and perception
 - situation assessment/awareness
 - decision-making
 - taking action
 - teaming with humans
 - and knowledge acquisition (learning)





Search and Rescue Mission

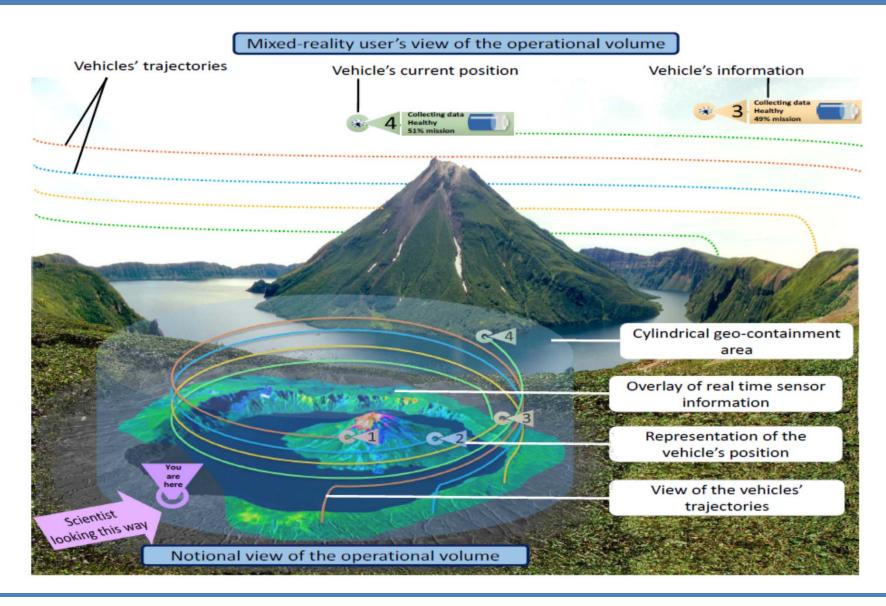






Notional Science Mission







Mars Mission: Sample Return

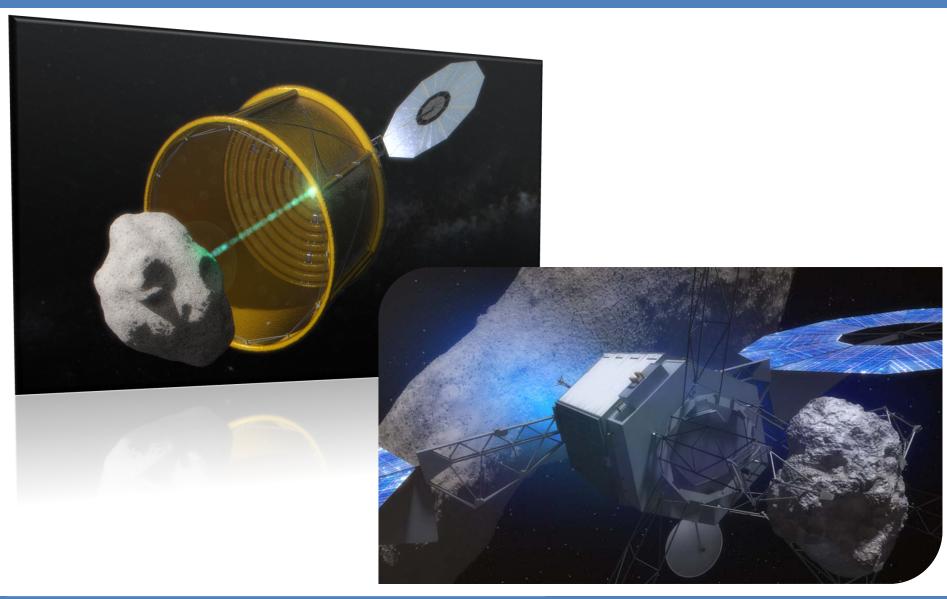






Asteroid Redirect Mission

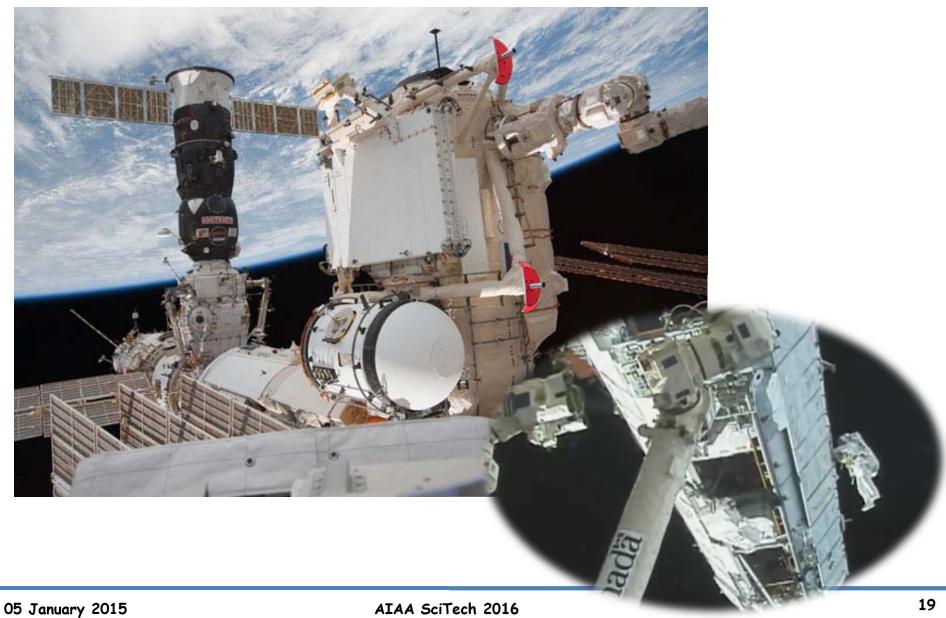






In-Space Assembly







AI: Three Goals & Many Challenges



1. Build a Multi-Disciplinary Team

- Mechanics/Electronics/
- Controls
- Computer Science/Programming
- Psychology/Human Factors
- Machine Learning
- Signal Processing/Computer Vision

2. Enable new missions in

- Space
- Aeronautics
- Science

3. Create a Testbed for Autonomous Systems

- Open Software Architecture (AEON)
 - Data Distribution Service (DDS)
- Langley Autonomy & Robotics Center
- CERTAIN



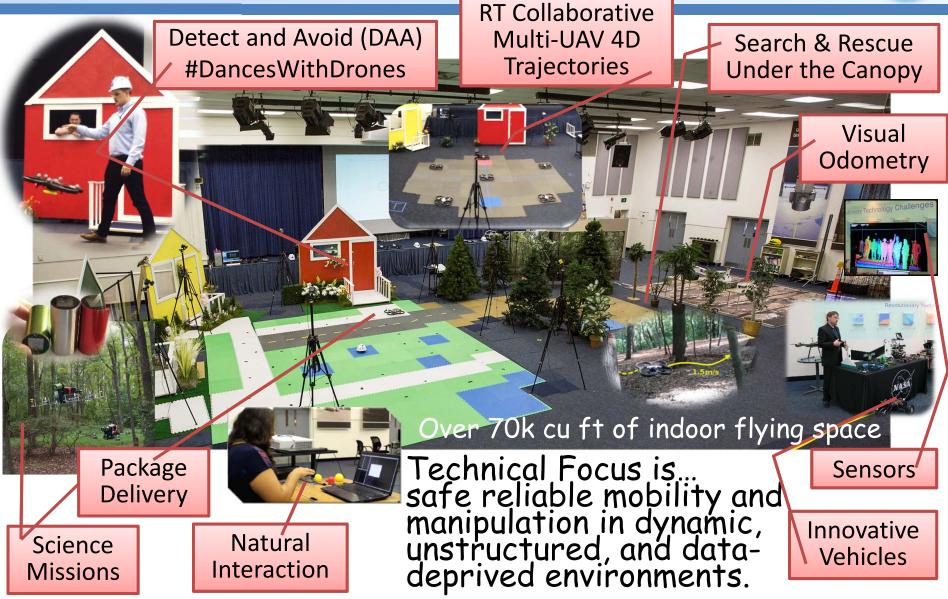
Autonomy Challenges

- Human-Machine Interaction
- Data-rich/degraded/deprived environments
- Size, Weight And Power (SWAP)
- Sensor Fusion
- Adaptive Control
- Geo-containment
- Sense/Detect and Avoid (DAA)
- Precision navigation
- Localization
- Adaptation and Learning
- Performance Standards
- Verification and Validation (V&V)
- Certification/Trust
- Test and Evaluation (T&E)



Autonomy Incubator R&D

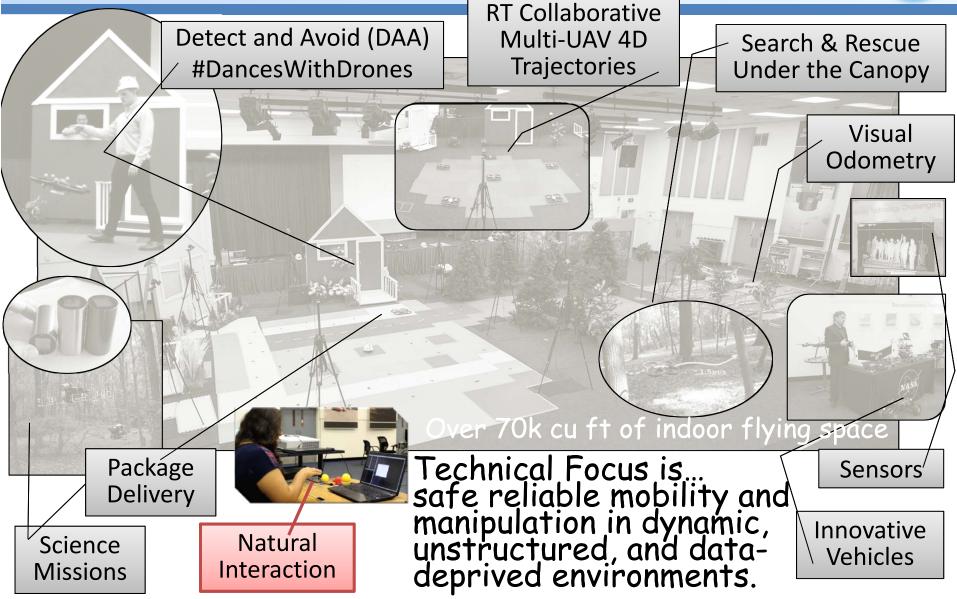






Autonomy Incubator R&D







Why We Need Natural Interaction



Develop a gesture-based natural language interface which non-expert users can quickly and easily use to define and fly trajectories for an autonomous, unmanned vehicle.

Application: Atmospheric Science Mission

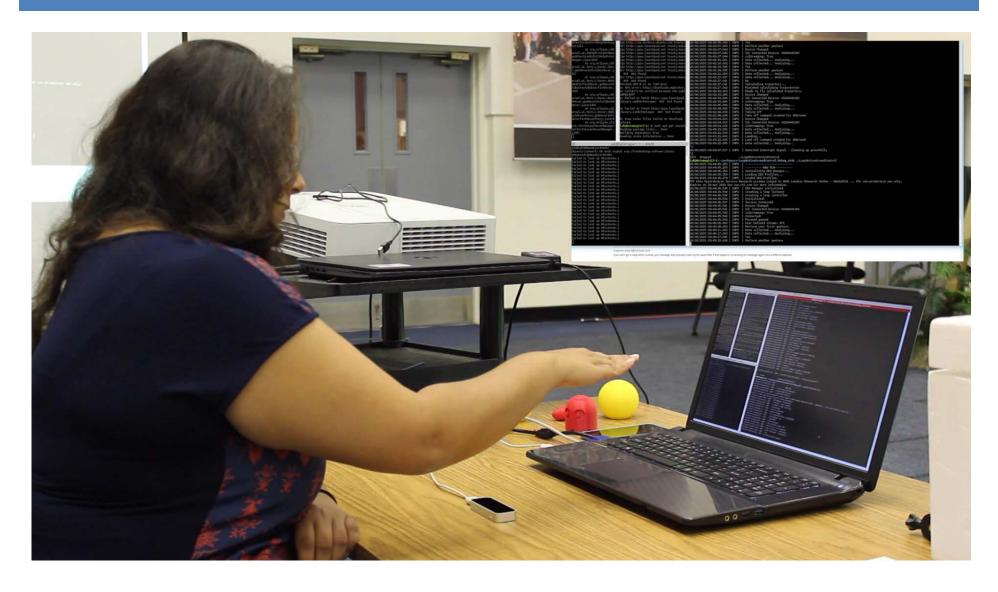
- Fly multiple vehicles
- Correlative data acquisition
- Intuitive interface
- DO NOT need low-level understanding of architecture or piloting expertise





Human Machine Teaming



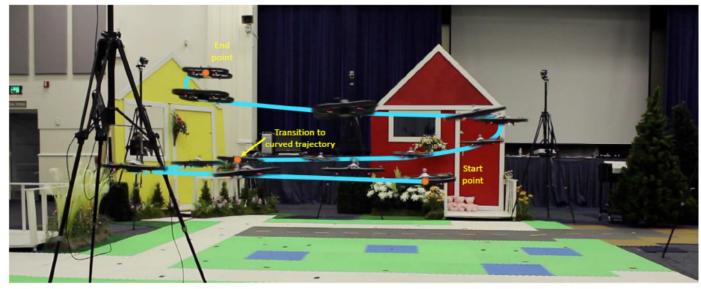




Using Gestures to Define Trajectories



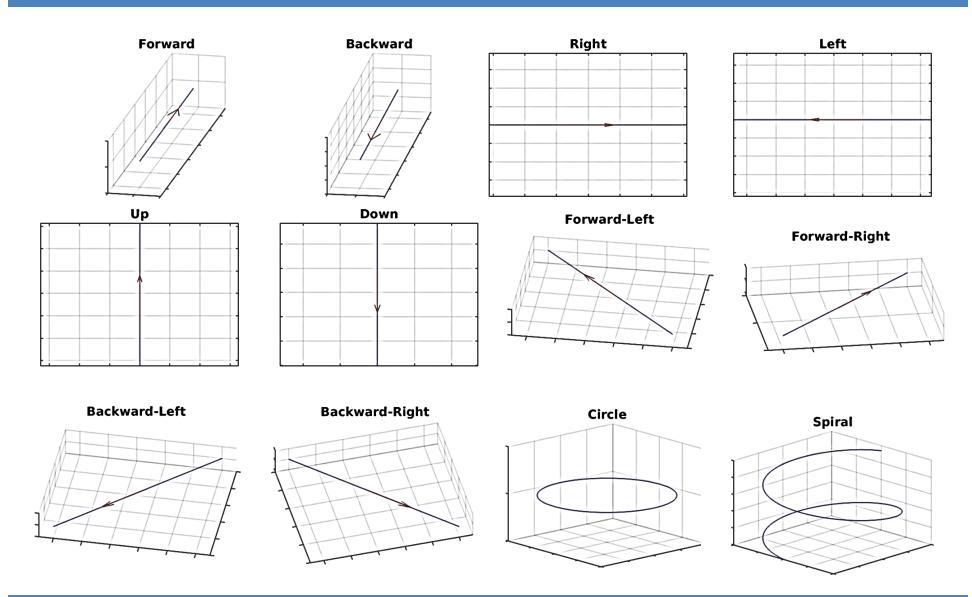






Gesture Library







3D Gesture Characterization



Spiral

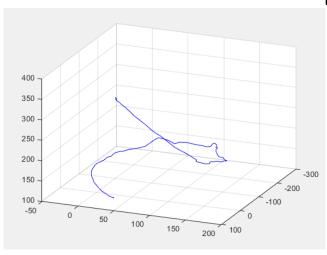
Threshold Raw Data

Method:

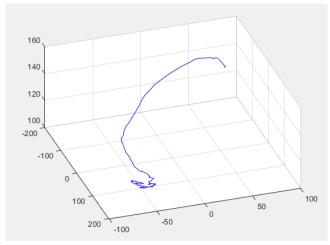
- Extract geometric features from raw data
- Create thresholds for geometric features such that the value is able to provide a characterization for the input gestures
- Fairly easy to implement

Disadvantages:

- Threshold values are based on a singular user
 - System will most likely incorrectly characterize gestures performed by other users



Forward-Right





ML-Based Characterization



Method

- 11 Subjects
- 10 samples per gesture
- Support Vector Machine (SVM) Classifier
 - Linear
- Features used:
 - Hand movement direction
 - Eigenvalues

Results

- ~5 users (in addition to initial user) were able to successfully use the interface with the gestures correctly characterized
- Required less than 5 minutes of training time

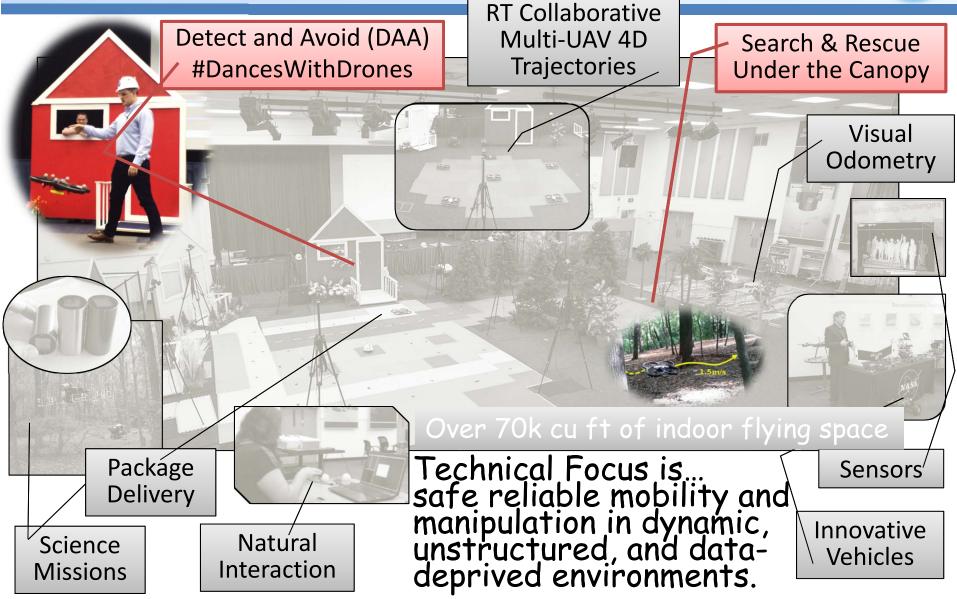
<u>Next</u>

- More training and users
- Evaluation at CMU and NASA LaRC
- Online learning of new trajectory types



Autonomy Incubator R&D







Earth Science Mission





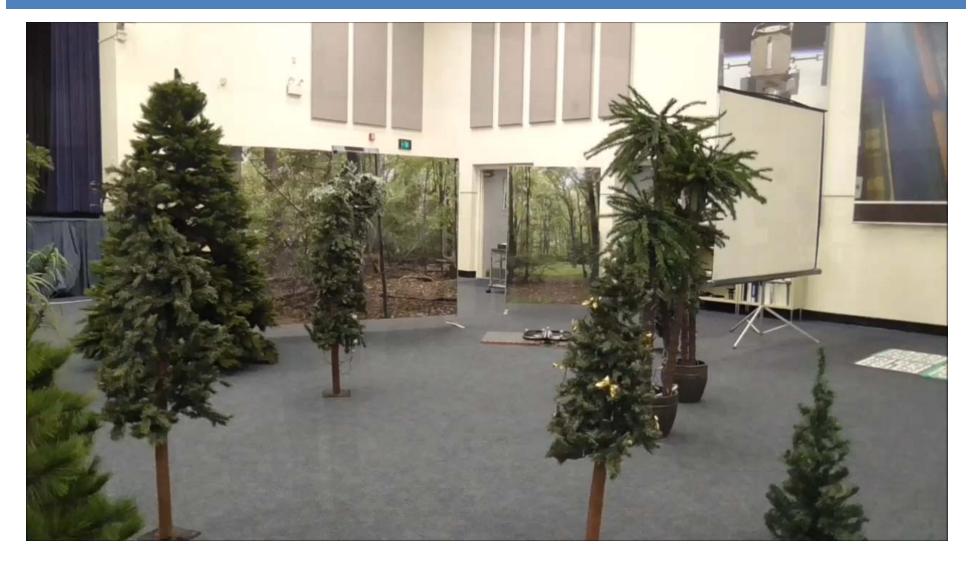
Air Quality Monitoring Sensors



Detect and Avoid

(#TreeDodging)

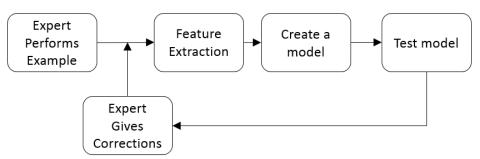






Tree Dodging





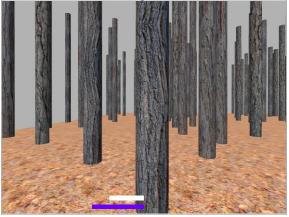


- Feature Extraction
 - Structure Tensors
 - Radon Transform
 - Laws' Masks
- Kernel Ridge Regression
 - Radial basis function for kernel
 - Model is created that relates visual features to a human pilot's commands
- User feedback is supplied for undesirable situations
 - New model is created and process iterates











Pilot Correction

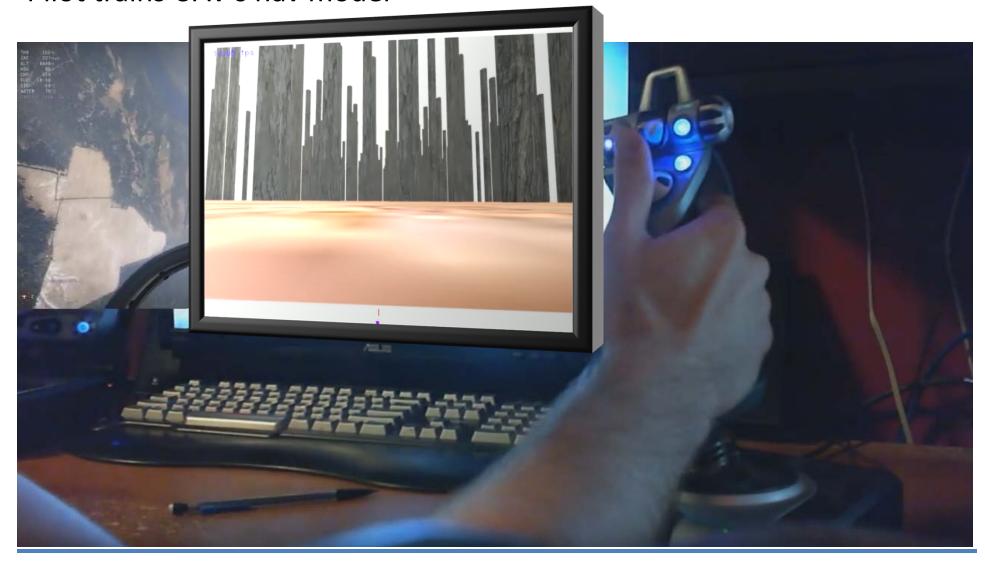
Algorithm



Reinforcement Learning



Pilot trains UAV's nav model





Obstacle Avoidance under Tree Canopy



- Potential applications:
 - Package delivery
 - Search and rescue
 - Science missions in cluttered environments
- Working with MIT



Algorithm







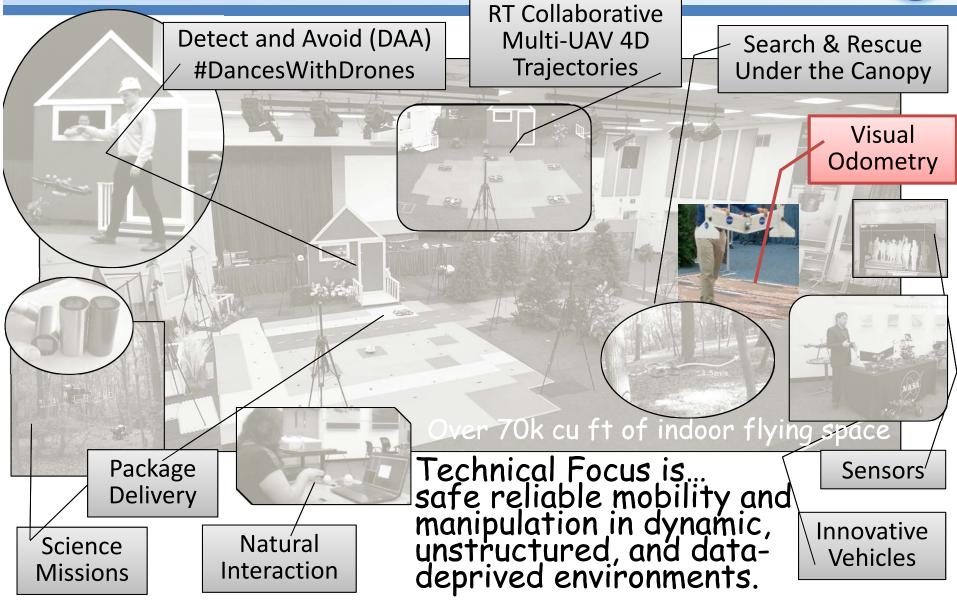
Object Avoidance / Path (re)planning (#DancesWithDrones)





Autonomy Incubator R&D







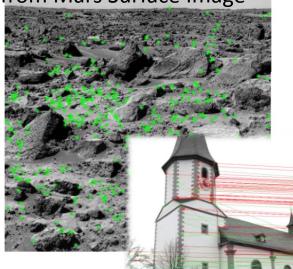
Data-Deprived Navigation



Mars Flyer









Fast Semi-Direct Monocular Visual Odometry (SVO) with **Fault Detection and Recovery** for localization and mapping

[C Forster, M Pizzoli, D Scaramuzza]

Working with GT

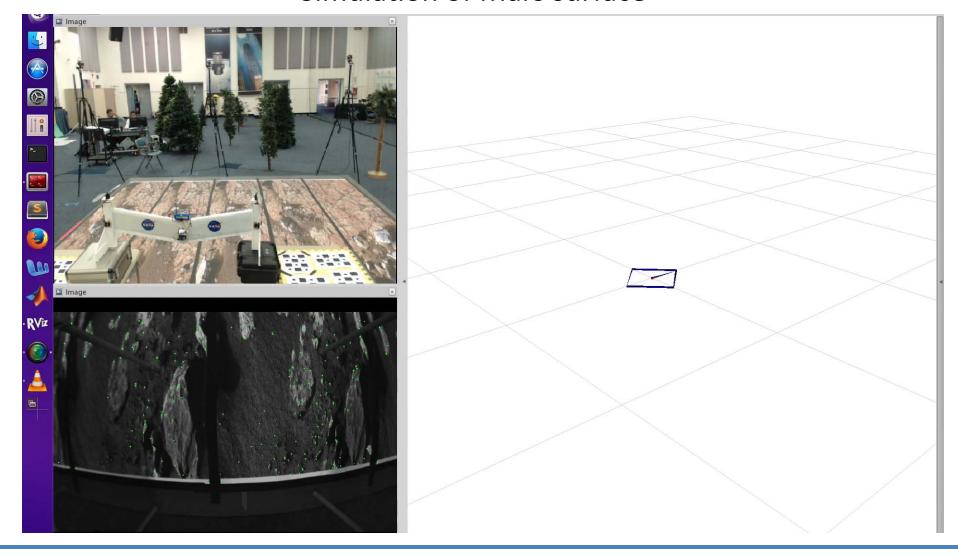
Feature Alignment



Robust Visual Odometry



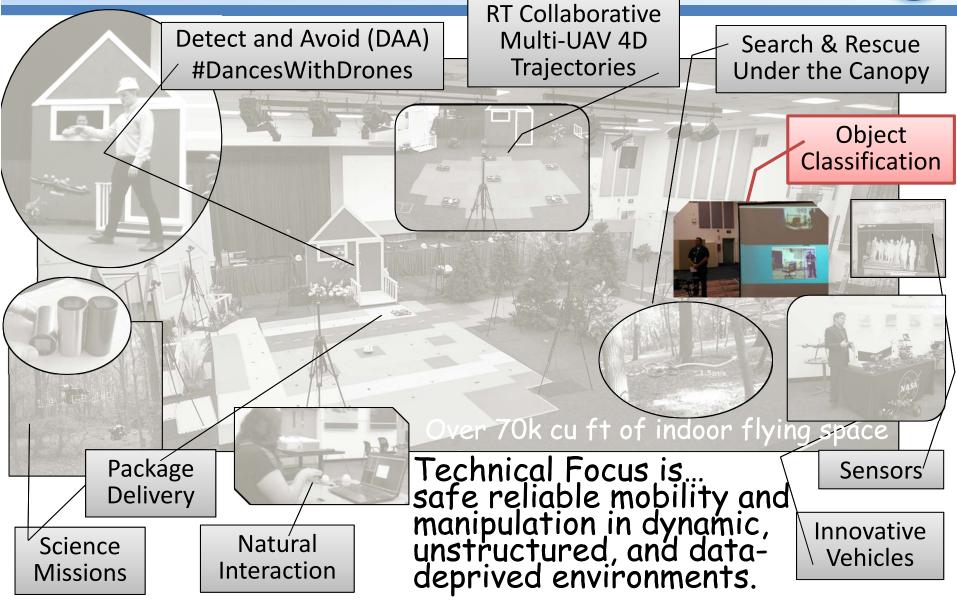
Simulation of Mars surface





Autonomy Incubator R&D







Object Detection & Classification



- CNN (Convolutional Neural Network)
 - train both a classification and a detection network
- LSDA (Large Scale Detection through Adaptation)
 - train a detector on datasets without bounding box data for all categories

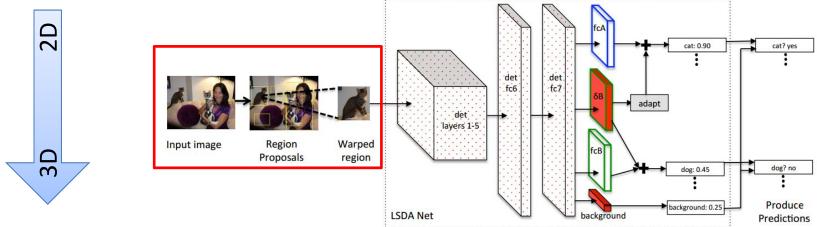


Figure. 2. Detection with the LSDA network. From: J. Hoffman, et al. (2014)

"LSDA: Large Scale Detection through Adaptation." NIPS 2014.

Alternate Segmentation Approach:

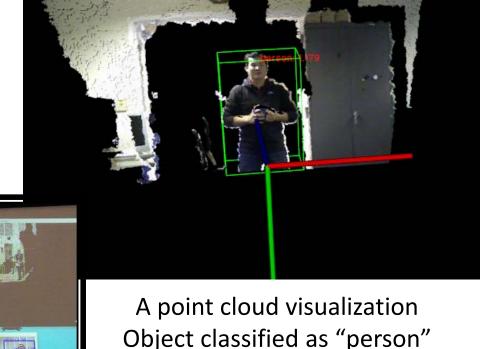
- RGB-D Camera point cloud
- Conversion from point cloud to image



3D Object Classification



- 3D Space Classification
 - Detect
 - Classify
 - Locate the object in 3D space



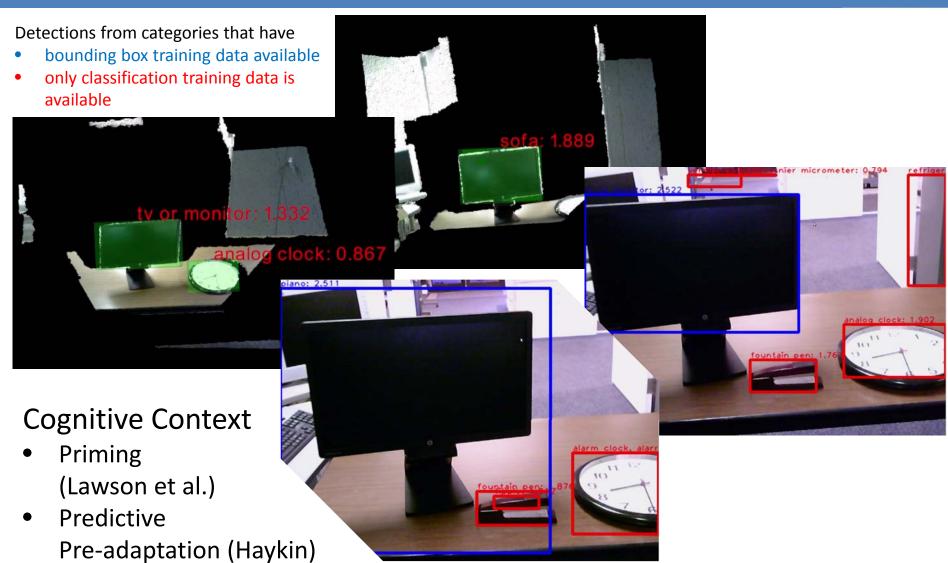
Object classified as "person"

Multiple objects classified: person and chair



Misclassifications

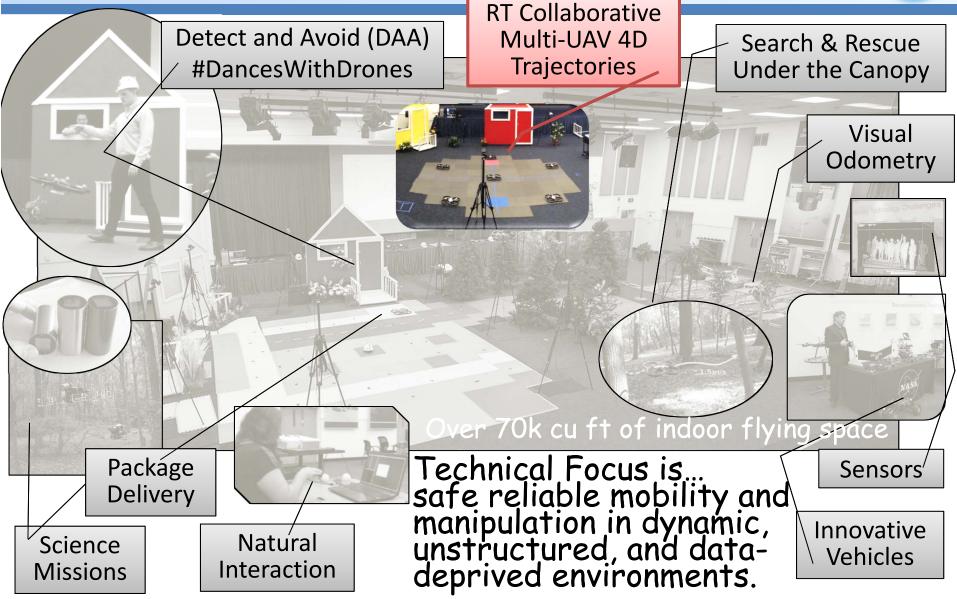






Autonomy Incubator R&D

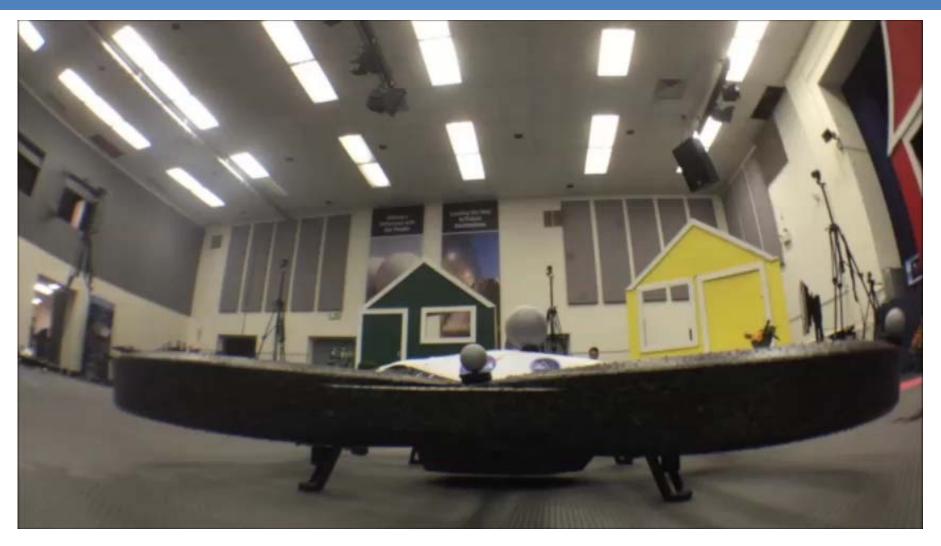






Multi-Agent Collaborative Trajectories





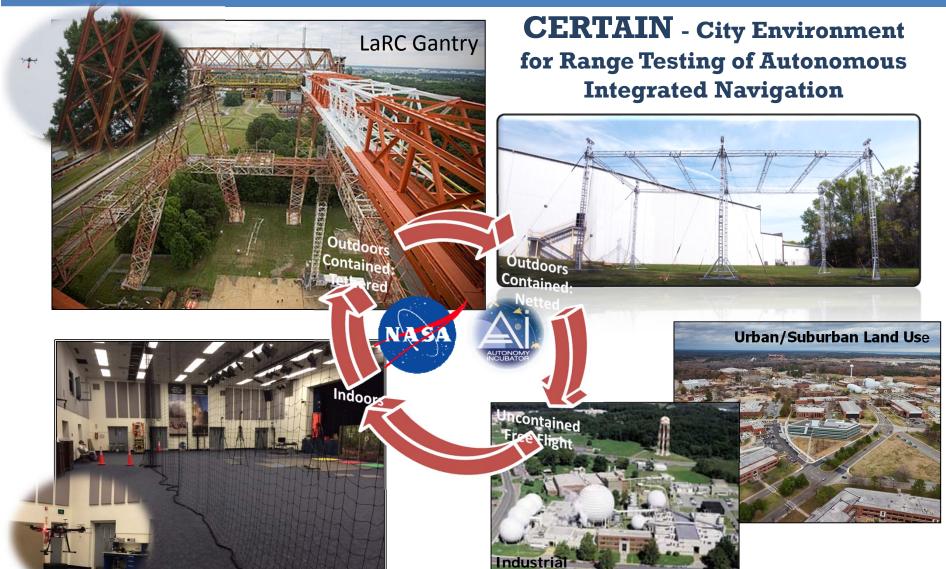
Working with UIUC

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Test & Evaluation





Facilities



CERTAIN Test Range







Package Delivery in LaRC COA Area

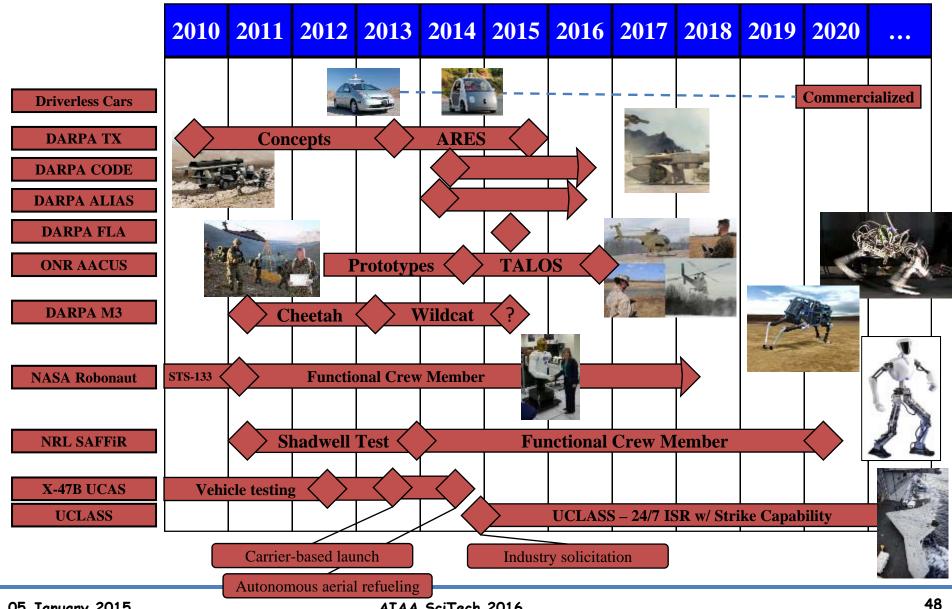






The Autonomy Frontier







Thank You



Blog: http://autonomyincubator.blogspot.com/

Twitter: @AutonomyIncub8r Instagram: @AutonomyIncubator



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NASA Langley Research Center

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